



## **An evolving experience learned for modelling thermal dynamics of buildings from live experiments: the Flexhouse story**

Power and Energy Systems Engineering

**Yu, Xingji; You, Shi; Jiang, Yuewen; Zong, Yi; Cai, Hanmin**

*Published in:*  
Energy Procedia

*Link to article, DOI:*  
[10.1016/j.egypro.2017.11.098](https://doi.org/10.1016/j.egypro.2017.11.098)

*Publication date:*  
2017

*Document Version*  
Publisher's PDF, also known as Version of record

[Link back to DTU Orbit](#)

### *Citation (APA):*

Yu, X., You, S., Jiang, Y., Zong, Y., & Cai, H. (2017). An evolving experience learned for modelling thermal dynamics of buildings from live experiments: the Flexhouse story: Power and Energy Systems Engineering. *Energy Procedia*, 141, 233-239. <https://doi.org/10.1016/j.egypro.2017.11.098>

---

### **General rights**

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

4th International Conference on Power and Energy Systems Engineering, CPESE 2017, 25-29  
September 2017, Berlin, Germany

# An evolving experience learned for modelling thermal dynamics of buildings from live experiments: the Flexhouse story

Xingji Yu<sup>a</sup>, Shi You<sup>a</sup> \*, Yuewen Jiang<sup>b</sup>, Yi Zong<sup>a</sup>, Hanmin Cai<sup>a</sup>

<sup>a</sup>Center for Electric Power and Energy, Technical University of Denmark, Elektrovej 325, DK-2800 Lyngby, Denmark

<sup>b</sup>College of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350116, Fujian, China

---

## Abstract

This paper shares an evolving experience learned for modelling the thermal dynamics of buildings from live experiments run in Flexhouse1 at Risø Campus of Technical University of Denmark (DTU). Among different trials, circuit based grey-box models approach have been developed and improved from time to time. Although the intension of modelling the thermal dynamics of Flexhouse1 remains unchanged, the details of experiments and applied modelling approach do evolve over time due to the increase of knowledge and the improvement made to the experimental platform. In addition to presenting a summary of these details, additional suggestions on future improvements are discussed and preliminarily investigated.

© 2017 The Authors. Published by Elsevier Ltd.

Peer-review under responsibility of the scientific committee of the 4th International Conference on Power and Energy Systems Engineering.

**Keywords:** buildings; grey-box models; thermal dynamics.

---

## 1. Introduction

The fast growth of intermittent renewables like wind power and solar has resulted in the need of multiple types of flexibility in the energy sector [1]. Today, buildings account for over one-third of total final energy consumption in the world [2]. A considerable portion of the energy consumed by buildings is used for heating, especially for countries like the Nordic countries whose winter is typically long and cold. Correspondingly, the thermal mass of buildings becomes an ideal storage-alike resource that can balance the fluctuation of intermittent renewables by

---

\* Corresponding author. Tel.: +45 61396266.

E-mail address: [sy@elektro.dtu.dk](mailto:sy@elektro.dtu.dk)

offering aggregation-based large scale flexibility at a very low cost [3]. Model-based understanding the thermal dynamics of buildings therefore plays an important element in exploring and utilizing the flexibility potential of buildings. The level of its important is the same as other key elements such as modelling occupant behavior and modelling various heating solutions.

#### Nomenclature

CTSM-R	Continuous Time Stochastic Modelling for R
DTU	Technical University of Denmark
LFM-TM	Latent force thermal model of the thermal dynamics of a building
PCA	Principal component analysis
PRBS	Pseudo random binary sequence
RC	Resistance and capacity
RMS	Random multi-setup sequences
SVD	Singular value decomposition
$n$	Maximum number of bits in PRBS
$T$	Single time period in PRBS
$D$	Periodic duration of one PRBS experiment

Methods applied to modelling the thermal dynamics of buildings can be classified to three main categories:

- Black-box modelling which is completely data-driven and only considers the inputs and the outputs of the system. It is normally applied in situations when there is either little knowledge of the system's physical property or the system is too complicated with many unknown influencing factors. Examples of black-box modelling are given by [4] wherein neural network is applied. Quality of black-box models are normally much dependent on the data collected from experiments which have to be designed carefully in order to collect a sufficient amount of representative data for estimating the dynamic behavior and validating the developed model.
- White-box modelling which requires all the details of the system, for instance, the physical structure (formulas of convection, ventilation, solar irradiance etc.) and the value of relevant parameters like heat capacity and thermal resistance of the materials of the building. Good examples of white-box modelling are presented in [5,6] where RC circuit network models are developed, provided the parameter values of building material are known in advance. The accuracy of models can always be improved when specific influencing factors such as the moisture inside the building as in [7] and ventilation and convection inside the building as in [8] are taken into account.
- Grey-box modelling is a combination of the former two approaches. It normally uses the prior physical knowledge to estimate the general physical structure of the model and then applies the experimental data to estimate the parameter value and to modify the model. Examples using differential equations to model the thermal dynamics are presented by [3, 9, 10], while RC circuit based models are also developed in [6, 11] using grey-box approach. Comparing the white-box model, models developed in [6, 11] the values of relevant parameters are estimated according to their maximum likelihood that were derived based on experimental data. Since the data-driven approach can be easily influenced by any noise signals, a latent force thermal model (LFM-TM) is introduced in [12] as an add-on to the original grey-box model in order to compensate for the deviation caused by unknown physical part and noise inside the system. As a result, the grey-box model with LFM-TM term will have a high likelihood for the data without having a too complicated structure of the model.

In this article, an evolving experience learned from a live experimental setup, i.e., Flexhouse1 at Risø Campus of Technical University of Denmark (DTU) is introduced. The experience collected for modelling the thermal dynamics of FlexHouse1 (an office building) using grey-box approach evolves over time as different experiments and studies were conducted based on this facility. A brief description of FlexHouse1 is presented in Section 2. Section 3 presents a detailed review of the modelling experience accumulated over time. Several suggestions for how to improve the existing models is discussed in Section 4. Section 5 presents discussion and conclusion.

## 2. An introduction to Flexhouse1

FlexHouse1 is an office building (also serving the temporary purpose of residential) located at the DTU Risø Campus. Together with another two Flexhouse, the three buildings play an important part in the SYSLAB experimental platform for demonstrating the flexibility of buildings in power and energy management [13]. The building area of FlexHouse1 is approximately 120m<sup>2</sup> and rests on concrete slabs. Several snapshots of FlexHouse1 are presented in Fig.1 to give a quick practical overview. Information about its layout, the walls (e.g., materials and thickness of walls and insulation layers) and the windows (e.g., size and orientation) etc., are available from its blueprint with some levels of details. Operational information of the house and the surrounding climate is collected through the indoor sensors (measuring temperature, motion, and energy consumption) and an outdoor climate station (measuring temperature, humidity, solar irradiation, direct and speed of wind) respectively. Electric heaters as the primary heating solution are installed in each room. A tailored building management solution not only performs a number of routines for the second by second data management and local control actions, but also allows for intelligent control/energy management solutions to be remotely implemented through a generic SYSLAB interface. Such design enables different system-level control architectures ranging from centralized to fully decentralized. One attention that needs to be paid to this experimental facility is the experiments conducted in the building should be prevented from situations with temperature exceeding 30 °C, if the control of electrical heaters is involved. This is because the heaters will shut down automatically due to the embedded thermostatic-based control logic. Further, the indoor temperature of FlexHouse1 is very sensitive to indoor and outdoor changes, which turns it into an ideal experimental site for understanding the influence introduced by different factors.



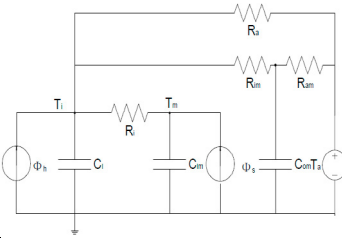
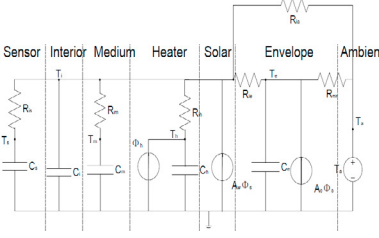
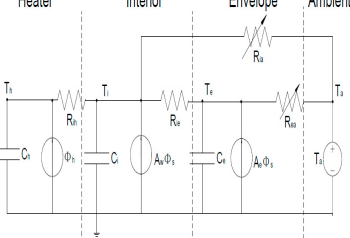
Fig.1. Snapshots of the Flexhouse1: (top-left) Air gap; (top-middle) Planks covering the air gap; (top-right) South façade; (bottom-left) North façade; (bottom-middle) Climate station; (bottom-right) Interior dimensions of the floor plan and sensor distribution

## 3. Evolving experience learned over time

Ever since 2008, a number of studies have been conducted to model the thermal dynamics of FlexHouse1 in order to accumulate the knowledge and experience. Although the intension of modelling the thermal dynamics of Flexhouse1 remains unchanged, the experiments and the modelling approach do evolve over time due to the increase of knowledge and the improvement made to the experimental platform over the years. Table 1 presents a short summary of three major experiments-based modelling activities which were conducted in 2008 [14], 2009 [15] and 2015 for some improvements [16]. Each experiment is made of a number of sub experimental activities. The time span between the two early experiments and the last experiment is quite long because many relevant studies

were performed in other Flexhouse buildings during that moment. However, the attention paid to Flexhouse1 and the intension of extending the existing knowledge and modeling experience have not changed.

Table 1. A brief over of selected experiments-based activities performed in Flexhouse1

	Experiment 2008	Experiment 2009	Experiment 2015
Model inputs	Power consumption of electrical heaters (estimated based on measured on/off status), solar irradiation, outdoor temperature.	Power consumption of electrical heaters (measured), solar irradiation, outdoor temperature.	Power consumption of electrical heaters (measured), solar irradiation, outdoor temperature, wind speed.
Model outputs	$T_i$ (indoor air temp.), i.e., single temp. value representing the indoor temp. of the building.	$T_i$	$T_i$
Data collection and excitation methods	Four PRBS experiments with input and output data measured every 5 minute for each experiment.	One PRBS experiment with three PRBS segments conducted in series.	One PRBS experiment.
Dimension reduction for indoor temp.	PCA, i.e. to reconstruct the eight measured indoor air temp. values per room through dimension reduction in order to achieve a single representative temp. value.	Average temp.	Average temp.
Excitation details	$n=6$ , $T=20\text{min}$ , $D=21\text{hr}$ .	$n=6$ , $T=20\text{min}$ , $D=21\text{hr}$ for the first two segments; $n=5$ , $T=3.5\text{hr}$ , $D=108.5\text{hr}$ for the 3 <sup>rd</sup> segment..	$n=6$ , $T=20\text{min}$ , $D=21\text{hr}$ .
State variables	$T_i$ , $T_e$ (temp. of the building envelope) and $T_m$ (temp. of an interior thermal medium, i.e. interior walls/floors).	$T_i$ , $T_h$ (temp. of electrical heaters) and $T_e$ , $T_m$ , $T_s$ (temp. of the sensor).	$T_i$ , $T_h$ , $T_{im}$ , $T_e$ and $W_s$ (wind speed).
Parameter estimation tool	CTSM in C++ for estimating the unknown RC values.	CTSM-R in R for estimating the unknown RC values.	CTSM-R in R for estimating the unknown RC values.
Model structure			
Major achievement	A simple stochastic linear state space model in discrete time of the heat dynamics that captures well the relatively low-frequency dynamics.	A generic model structure for linear thermal dynamics models of buildings, allowing for models to be developed with different level of complexity.	A non-linear heat dynamic model with air infiltration with significant improvement of accuracy.

In all these experiments, the RC circuit-based grey-box modeling approach is selected over the other approaches due to information unknown (like the thermal resistance and heat capacity of different components in and parts of the buildings) and limited duration for each experiment. Pseudo random binary signals (PRBS) are applied to excite the system in all experiments. In order to reduce the level of complexity, dimension reduction approaches are applied, wherein the measured indoor air temperature per room is reconstructed by through principal component analysis (PCA) or simply using the average temperature. Parameter estimation for all experiments is based on maximum likelihood value performed by tools developed for continuous time stochastic modelling (CTSM)[17], although implemented in different software platforms. Different models developed in each experiment are statistically compared to each other using likelihood ratio tests in order to find a final model with the best

performance. An obvious fact that can be found is the increasing level of complexity, i.e., to include more relevant state variables and properties into the model even with nonlinear representations.

The first trial performed in 2008 developed a simple stochastic linear state space model in discrete time that captured well low frequency dynamic behaviors, provided the information available by then. Communication failures and hardware issues to a large degree limit the quality and sufficiency of data that was applied to model development.

The experiment 2009, based on a significant improvement of the experiment infrastructure, managed to record a much better building energy performance data in the winter period of 2009. This enables a better modelling experience based on relatively sufficient information, such as the power consumption of each electrical heater is measured. The forward selection strategy designed followed a clear process, i.e., to add new components to a simple RC model step by step to increase the likelihood function. This stopped when the calculated probability p-values were greater than 0.05, implying the change made does not improve the model. As illustrated in Table 1, the full model structure developed by experiment 2009 in principle can include all possible components in and parts of the building. In addition to presenting a relatively generic model structure, the investigation pointed out the performance of models would not be further improved when the complexity reached a certain level. For this specific experiment, the best model was found with an order of three. The recent experiment in 2015 is an extension of the previous ones by including non-linear effects (caused by forced ventilation or infiltration in a thermally light building) and wind speed into the model. This exercise showed some significant improvements of the model performance, when it is compared with the early developed ones.

#### 4. Potential extensions of the developed models

Although the performance of the developed models has been improved over time, there are still many possibilities to improve individual element (i.e. the first column of Table 1) of a modelling experiment in order to improve the developed model.

One trial, for instance, that can be made is to conduct more experiments for collecting high-quality data with longer durations. This would to a large degree compensate for the shortcomings of experiments performed in limited durations. Selection of process excitation methods is also necessary to be tested. For instance, PRBS is an open-loop excitation approach that is sensitive to disturbances and more preferable for linear process modelling. Similar approach such as random multi-setup sequences (RMS) can fit the requirements of both linear and nonlinear process modelling. Further, different designs of excitation signals are also worthy of further investigation. The current design of PRBS, i.e. the selection of  $n$  and  $T$  values, is rule of thumb-based to excite the heat dynamics at several ranges of frequencies in which the time constants of the building is expected to be. As the time constants could change over time due to material degradation and renovation, step-response testing needs to be performed from time to time to refine the estimated values.

Dimension reduction as the way to reduce complexity and to avoid overfitting issues is applied in all experiments, but keeping the dimension as original (i.e. to model all individual rooms instead of a lumped model) may also worth being investigated. One of the investigations made in [3] for modelling the thermal dynamics another Flexhouse at DTU Risø proved the potential benefits of having a multi-room/floor model instead of the lumped one. In case dimension reduction is under consideration, alternative methods to PCA or simply using the average value can also be considered. Fig.2 illustrates one example that applies singular value decomposition (SVD) for dimension reduction using the data collected in the 2009 experiment. When this change is implemented as the only change in the 2009 experiment, the resulted best third-order model can increase the likelihood from 5516.38 to 5560.89, i.e., around 1% performance improvement comparing to the performance of finally selected in 2009.

The results achieved by two other extensions of the best 2009 model are presented in Fig. 3. The top figures show the results achieved when include wind speed in the model, based on the hypothesis made in 2015 experiment that air infiltration is an influencing factor. However, the results achieved do not indicate any improvement, comparing to the best result achieved in 2009. The bottom figures in Fig.3 illustrate the results achieved when try to model the influence of solar radiation angle. The hypothesis behind is drawn from the fact that the effect of the solar radiation can not be fully characterized by a just multiplication between the effective window area (a constant) and the solar radiation measured from the climate station. Following the move of the sun, the amount of heat transferred

from solar radiation can be affected by the angle of the sun. This effect is modeled as a linear function that tries to represent the efficiency of the solar radiation at different time of a day. Although model achieved showed no further improvement to the best model achieved before, this idea is worthy to being further developed by having more sufficient data and more appropriate representation of the influence of sun angle.

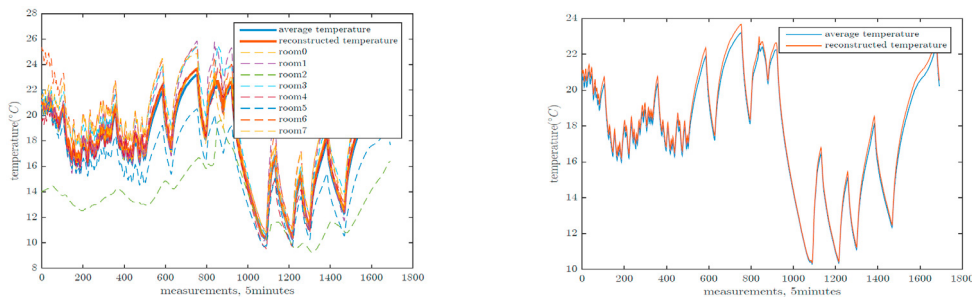


Fig.2. An illustration of applying SVD to dimension reduction in the 2009 experiment: (left) Comparison between reconstructed value and the individual room temperature; (right) A closer look at the difference between reconstructed value and the average temperature.

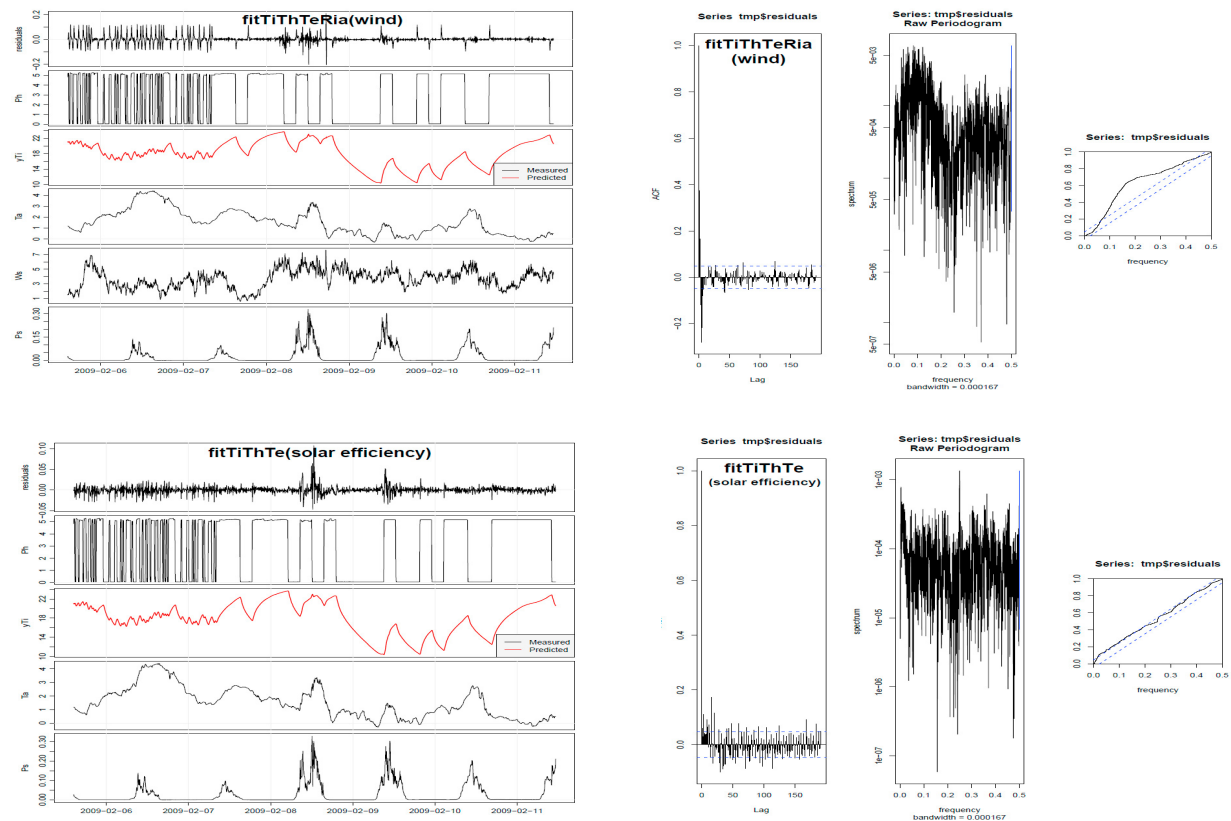


Fig.3. Results achieved by two model extensions: (top-left) Plot of the variables and comparison of the predicted temperature and temperature collected by sensors when include the wind speed; (top-right) Plot of residual and periodogram when include the wind speed; (bottom-left) Plot of the variables and comparison of the predicted temperature and temperature collected by sensors when include the angle of sun; (bottom-right) Plot of residual and periodogram when include the angle of sun



## 5. Discussion and conclusion.

The paper presented an evolving experience learned for modelling the thermal dynamics of buildings from live experiments. Among different trials, circuit based grey-box models approach have been developed and improved over the from time to time. For grey-box models, a careful design of experiments is always the key to developing high-quality models. Such carefulness shall be paid, in principle, to all influencing factors, which turned out to be very challenging. Several new extensions have been made to the early models in this study. Although the improvement turns out to be little, the experience learned may inspire other modelers to find better alternatives. Further, it has been well observed the increase of complexity can not always guarantee a satisfied increase of performance. The design of experiments and the final selection criteria among different models shall consider well the application-oriented requirements of any model to be developed.

## Acknowledgements

The authors would like to acknowledge the two Sino-Danish projects PROAIN and EMPIMES for their financial support. Sincere appreciation also goes to Dr. Anders Thavlov and Dr. Peder Bacher for their generosity in knowledge sharing.

## References

- [1] You S, Jin L, Zong Y, Bindner HW. The Danish perspective of energy internet: from service-oriented flexibility trading to integrated design, planning and operation of multiple cross-sectoral energy systems. *Zhongguo Dianji Gongcheng Xuebao*. 2015;35(14):3470-81.
- [2] IEA. Transition to Sustainable Buildings: Strategies and Opportunities to 2050. 2013.
- [3] Zong Y, Böning GM, Santos RM, You S, Hu J, Han X. Challenges of implementing economic model predictive control strategy for buildings interacting with smart energy systems. *Applied Thermal Engineering*. 2017 Mar 5;114:1476-86.
- [4] Gouda MM, Danaher S, Underwood CP. Application of an artificial neural network for modelling the thermal dynamics of a building's space and its heating system. *Mathematical and Computer Modelling of Dynamical Systems*. 2002 Sep 1;8(3):333-44.
- [5] Ramallo-González AP, Eames ME, Coley DA. Lumped parameter models for building thermal modelling: An analytic approach to simplifying complex multi-layered constructions. *Energy and Buildings*. 2013 May 31;60:174-84.
- [6] Hudson G, Underwood CP. A simple building modelling procedure for MATLAB/SIMULINK. In *Proceedings of the International Building Performance and Simulation Conference, Kyoto Japan 1999 Sep* (Vol. 2, pp. 777-783).
- [7] Lü X. Modelling of heat and moisture transfer in buildings: II. Applications to indoor thermal and moisture control. *Energy and buildings*. 2002 Nov 30;34(10):1045-54.
- [8] Perera DW, Pfeiffer CF, Skeie NO. Modelling the heat dynamics of a residential building unit: Application to Norwegian buildings. *Modeling, Identification and Control*. 2014 Jan 1;35(1):43.
- [9] Madsen H. Estimation of continuous-time models for the heat dynamics of a building. *Energy and Buildings*. 1995 Mar 31;22(1):67-79.
- [10] Andersen KK, Madsen H, Hansen LH. Modelling the heat dynamics of a building using stochastic differential equations. *Energy and Buildings*. 2000 Jan 31;31(1):13-24.
- [11] Ramallo-González AP, Eames ME, Coley DA. Lumped parameter models for building thermal modelling: An analytic approach to simplifying complex multi-layered constructions. *Energy and Buildings*. 2013 May 31;60:174-84.
- [12] Ghosh S, Reece S, Rogers A, Roberts S, Malibari A, Jennings NR. Modeling the Thermal Dynamics of Buildings: A Latent-Force-Model-Based Approach. *ACM Transactions on Intelligent Systems and Technology (TIST)*. 2015 Mar 11;6(1):7.
- [13] Gehrke O, Bindner H. Building a test platform for agents in power system control: Experience from SYSLAB. In *Intelligent Systems Applications to Power Systems, 2007. ISAP 2007. International Conference on 2007 Nov 5* (pp. 1-5). IEEE.
- [14] Thavlov A. Dynamic optimization of power consumption (Master's thesis, Technical University of Denmark, Lyngby, Denmark).
- [15] Bacher P, Madsen H. Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*. 2011 Jul 31;43(7):1511-22.
- [16] Thavlov A, Madsen H. A non-linear stochastic model for an office building with air infiltration. *International Journal of Sustainable Energy Planning and Management*. 2015 Nov 20;7:55-66.
- [17] <http://www.imm.dtu.dk/~ctsm/>